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How does spatial variability of climate affect catchment streamflow predictions?

Sopan D. Patil[1,2], Parker J. Wigington Jr.[3,4], Scott G. Leibowitz[3], Eric A. Sproles[1,5], Randy L. Comeleo[3]

[1] ORISE, c/o U.S. Environmental Protection Agency,

200 SW 35th St., Corvallis, OR 97333, USA

[2] School of Environment, Natural Resources and Geography,

Bangor University,

Deiniol Road, Bangor, LL57 2UW, United Kingdom

[3] Western Ecology Division,

National Health and Environmental Effects Research Laboratory,

U.S. Environmental Protection Agency,

200 SW 35th St., Corvallis, OR 97333, USA

[4] Retired

[5] Centro de Estudios Avanzados en Zonas Áridas

Universidad de La Serena

Raul Bitran s/n, La Serena, Chile

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Correspondence to: s.d.patil@bangor.ac.uk

Highlights:

1) We compare lumped and distributed hydrologic models at 41 catchments in northwest USA.

2) Distributed model performs better in catchments with low moisture homogeneity.

3) Spatial variability of precipitation phase is important in homogenous catchments.

Abstract

Spatial variability of climate can negatively affect catchment streamflow predictions if it is not explicitly accounted for in hydrologic models. In this paper, we examine the changes in streamflow predictability when a hydrologic model is run with spatially variable (distributed) meteorological inputs instead of spatially uniform (lumped) meteorological inputs. Both lumped and distributed versions of the EXP-HYDRO model are implemented at 41 meso-scale (500 – 5000 km^2) catchments in the Pacific Northwest region of USA. We use two complementary metrics of long-term spatial climate variability, moisture homogeneity index (I_M) and temperature variability index (I_{TV}), to analyze the performance improvement with distributed model. Results show that the distributed model performs better than the lumped model in 38 out of 41 catchments, and noticeably better (>10% improvement) in 13 catchments. Furthermore, spatial variability of moisture distribution alone is insufficient to explain the observed patterns of model performance improvement. For catchments with low moisture homogeneity ($I_M < 80\%$), I_M is a better predictor of model performance improvement than I_{TV}; whereas for catchments with high moisture homogeneity ($I_M > 80\%$), I_{TV} is a better predictor of performance improvement than I_M. Based on the results, we conclude that: (1) catchments that have low homogeneity of moisture distribution are the obvious candidates for using spatially distributed meteorological inputs, and (2) catchments with a homogeneous moisture distribution benefit from spatially distributed meteorological inputs if they also have high spatial variability of precipitation phase (rain vs. snow).

Keywords: Hydrologic model, climate variability, streamflow, catchment

1 Introduction

Meteorological inputs such as precipitation, air temperature, and potential evapotranspiration in spatially lumped hydrologic models consist of one-dimensional time series data. These data are obtained either from a single meteorological station located within the catchment [*Segond et al.*, 2007; *Vaze et al.*, 2011], from spatial interpolation of multiple meteorological stations in the region [*Arnaud et al.*, 2002; *Chaubey et al.*, 1999; *Tobin et al.*, 2011], or from an areal mean of meteorological data grids that cover the catchment's drainage area [*Koren et al.*, 1999; *Patil and Stieglitz*, 2014]. An important assumption in these models is that the one-dimensional inputs are uniformly distributed over the entire catchment. Numerous studies have shown that the quality of meteorological data used has a direct influence on the quality of modeled streamflow predictions [*Andréassian et al.*, 2001; *Bárdossy and Das*, 2008; *Faurès et al*., 1995; *McMillan et al.*, 2011; *Obled et al.*, 1994; *Vaze et al.*, 2011]. *Andréassian et al.* [2001] studied the impact of rain gage density on streamflow predictability at three catchments in France and found that the performance of rainfall-runoff models was directly proportional to the rain gage density used to generate the rainfall input. *Oudin et al.* [2006a] studied the effect of random and systematic errors in climate input data on streamflow predictions at 12 US catchments and found that random errors in rainfall series significantly affect the model performance; however, systematic errors in potential evapotranspiration series had greater impact on model performance than random errors. In Australia, *Vaze et al.* [2011] observed improved performance in hydrologic models when rainfall estimates were obtained from a gridded meteorological dataset compared to a single rain gage or a Thiessen weighted average of multiple rain gages.

Regardless of the data preparation technique, a spatially uniform representation of meteorological inputs has the potential to introduce significant uncertainty in catchments with high spatial variability of climate, and can negatively affect streamflow predictability [*Bárdossy and Das*, 2008; *Chaubey et al.*, 1999; *Moulin et al.*, 2009; *Shen et al.*, 2012]. Spatial variability in rainfall can affect the estimation of hydrologic properties such as peak flow magnitude and timing, stream flow volume, and soil moisture condition [*Arnaud et al.*, 2002; *Beven and Hornberger*, 1982; *Krajewski et al.*, 1991; *Nicótina et al.*, 2008; *Tramblay et al.*, 2011]. On the other hand, spatial variability in air temperature can affect the estimation of properties such as snow cover extent, snow storage magnitude, and snowmelt timing [*Jefferson*, 2011; *Leibowitz et al.*, 2012; *Nolin and Daly*, 2006; *Sproles et al.*, 2013]. Nonetheless, the degree to which spatial variability of climate affects catchment streamflow predictions is not fully understood.

Hydrologic models that use spatially distributed meteorological data (henceforth referred to as distributed models) are better equipped than those that use spatially uniform meteorological data (henceforth referred to as lumped models) to handle the spatial variability of climate. However, studies that have compared the lumped and distributed models provide a mixed picture on the perceived advantage of distributed models. For instance, model comparisons using theoretical approaches (e.g., virtual experiments) have typically been more favorable towards distributed models [*Andréassian et al.*, 2004; *Krajewski et al.*, 1991; *Wilson et al.*, 1979; *Zhao et al.*, 2013]. *Andréassian et al.* [2004] introduced the concept of chimera watersheds in which multiple combinations of the data from real watersheds are used to create a large number of virtual 'chimera' watersheds so that more heterogeneity can be obtained than is present in the existing data. Using these chimera watersheds, *Andréassian et al.* [2004] showed that distributed models provide much better simulation performance than lumped models. *Zhao et al.* [2013]

performed virtual experiments on 60 catchments in southeast Australia by systematically varying the spatial variability of rainfall in each catchment (while still preserving the total rainfall volume). The authors concluded that "for a given rainfall total, ignoring spatial rainfall variability will result in underestimation of the total streamflow volume and overestimation of evapotranspiration". In contrast, studies that have used real catchment data show that in most cases, only marginal improvements in streamflow predictions are obtained with distributed models compared to lumped models [*Boyle et al.*, 2001; *Das et al.*, 2008; *Refsgaard and Knudsen*, 1996; *Vaze et al.*, 2011]. *Reed et al.* [2004] summarized multiple results from the Distributed Model Intercomparison (DMIP) initiative and concluded that in most of the DMIP catchments, lumped models performed equally well or even slightly better than the distributed models. Similar results were shown by *Khakbaz et al.* [2012] in the newer DMIP 2 study. Thus, in spite of numerous studies comparing lumped and distributed models, we still cannot fully differentiate the types of catchments that will truly benefit from the use of distributed models in order to achieve improved streamflow predictability.

In this paper, our goal is to better understand the climatic conditions of catchments for which a distributed model does (or does not) provide better streamflow predictions than a lumped model. Both lumped and distributed versions of the Exponential Bucket Hydrologic Model (EXP-HYDRO) [*Patil and Stieglitz*, 2014] are applied at 41 meso-scale catchments (500 – 5000 km^2) in the Pacific Northwest region of USA. We begin with an *a priori* expectation that, in the absence of any additional information, the distributed model will have the same streamflow prediction capability as the lumped model at all catchments. For each catchment, we then determine whether any improvement occurs with the use of the distributed model and analyze this performance improvement within the context of long-term spatial climate variability in the catchment. We characterize the spatial climate variability in all catchments by using two different metrics, viz., moisture homogeneity index and temperature variability index.

2 Study Area and Data

Our study area is in the Pacific Northwest (PNW) region of USA and covers the states of Oregon, Washington, and Idaho (Figure 1). Within these three states, we select 41 catchments that satisfy the following two criteria: (1) they belong to either the HCDN [*Slack et al.*, 1993] or GAGES [*Falcone et al.*, 2010] database of the U.S. Geological Survey (USGS), and (2) their drainage areas are within the 500 to 5000 km^2 range. The selection from HCDN and GAGES databases is done to ensure that the hydrologic regimes of the catchments are minimally impacted by anthropogenic effects. The specified range limit of drainage areas is to ensure that the catchments are large enough to detect spatial climate variability within them, but small enough to ignore the delays in streamflow response due to channel network routing. The drainage area of the catchments varies from 518 km^2 to 4956 km^2, with the median drainage area of 865 km^2. The mean annual precipitation in the catchments varies from 540 mm to 3615 mm, with the median value of 1251 mm. Of the 41 chosen catchments, 20 are located in Oregon, 7 are located in Washington, and 14 are located in Idaho (see Figure 1).

Climate of the PNW region is highly influenced by large scale atmospheric circulation patterns caused by the presence of Pacific Ocean to the west and the subsequent interaction of these patterns with the Cascade and Rocky Mountain ranges [*Salathé et al.*, 2008]. This interaction creates a strong climate gradient in the west-to-east direction. The western parts of the PNW, between the Pacific Ocean and the Cascade Mountains, experience high amounts of rainfall and mild temperatures due to the maritime climate influence [*Wigington et al.*, 2013].

The eastern parts, between the Cascade and Rocky Mountains, are much drier because of the rain-shadow effect of the Cascade Mountains and experience more extreme intra-annual temperature differences. Roughly two-thirds of the precipitation in the PNW occurs during the colder October to March period, while most of the region typically experiences dry summers. Annual precipitation amounts and temperature are further influenced by the long term climate trends caused by the El Niño Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) [*Brown and Kipfmueller*, 2011; *Cayan*, 1996]. Due to high elevations of the Cascades and the Rockies, a significant amount of precipitation (much of it snow) is captured in the region’s mountains. As a result, the hydrology of major rivers in this region (e.g., Columbia, Snake, and Willamette) is dominated by snow accumulation in the winter season and snowmelt in the spring season [*Hamlet and Lettenmaier*, 1999; *Regonda et al.*, 2005; *Safeeq et al.*, 2013].

We use the daily streamflow data from USGS stream gages that are located at the outlet of all 41 catchments. The time-span of the streamflow and meteorological input data is 20 years, ranging from water year 1971 to 1990 (i.e., 1st October, 1970 to 30th September 1990). Daily data of the meteorological inputs (precipitation and air temperature) is obtained from the gridded observed meteorological dataset developed by *Maurer et al.* [2002]. This dataset has the spatial resolution of 0.125 degrees (about 100 km^2 grid) and covers the entire continental United States. Given that our smallest study catchment has a drainage area of 518 km^2, the ratio of the meteorological grid resolution to basin size is less than 0.2 for all catchments. The methods used to obtain the lumped and distributed versions of precipitation and air temperature inputs from the gridded dataset for each catchment are described in Section 3.2. Daily potential evapotranspiration inputs (both lumped and distributed version) are calculated directly from the daily air temperature data using Hamon’s formula [*Hamon*, 1963]. For calculation of the two climate variability metrics at each catchment (see Section 3.3 for further details), we use the 30-year (1971-2000) average values of precipitation, air temperature, and potential evapotranspiration that are derived from the long-term data of Climate Source, Inc. (http://www.climatesource.com/us/fact_sheets/fact_tmean_us_71b.html). This commercially available data has a resolution of 400 m and covers the entire continental United States (see *Wigington et al.* [2013] for details).

3 Methods

3.1 Hydrologic model

The EXP-HYDRO model was originally developed by *Patil and Stieglitz* [2014] as a spatially lumped hydrologic model that operates at a daily time-step. In this paper, we have used the original lumped version of the model as well as a modified version that explicitly accounts for spatially distributed meteorological inputs (see section 3.2 for details). Below, we provide a brief description of the model.

The EXP-HYDRO model conceptualizes a catchment as a bucket store that receives water inputs in the form of liquid precipitation and snowmelt and has water outputs in the form of evapotranspiration, subsurface runoff, and capacity-excess surface runoff (Figure 2). Daily precipitation is first classified as either rainfall or snowfall, depending on the day's air temperature. Snowfall accumulates separately into the snow accumulation bucket, whereas the rainfall is input directly into the catchment bucket. Snowmelt from the snow accumulation bucket is modeled using a thermal degree-day model, and the melt runoff generated is used as an input to the catchment bucket. The amount of evapotranspiration in the catchment is calculated as a fraction of potential evapotranspiration and depends on the ratio of actual water stored in the catchment bucket on the given day to the catchment bucket's storage capacity. Subsurface runoff depends on the amount of water stored in the catchment bucket and is calculated using a TOPMODEL [*Beven and Kirkby*, 1979] type exponential equation. Capacity-excess surface runoff occurs once the catchment bucket is filled to its capacity and there is still some excess amount of water from the rainfall and snowmelt inputs. Catchment streamflow is calculated as the sum of subsurface runoff and capacity-excess surface runoff. Detailed description of the mathematical formulas of this model can be found in *Patil and Stieglitz* [2014] and *Patil et al.* [in press].

There are six free calibration parameters in the EXP-HYDRO model: f, S_{max}, Q_{max}, D_f, T_{max}, and T_{min}. The parameter f (unit: 1/mm) controls the rate of decline in subsurface runoff from the catchment bucket as its storage level fluctuates. S_{max} (unit: mm) is the maximum storage capacity of the catchment bucket. Q_{max} (unit: mm/day) is the maximum subsurface runoff that occurs when the catchment bucket is full. D_f (unit: mm/day/°C) is the thermal degree-day factor that controls the rate of snowmelt from the snow bucket. T_{max} (unit: °C) is the air temperature above which snow starts melting, whereas T_{min} (unit: °C) is the air temperature below which precipitation falls as snow. We calibrate these parameters for each catchment with 50,000 Monte Carlo simulations [*Vaché and McDonnell*, 2006]. Parameter ranges used for the random sampling of all six parameters are the same as those in *Patil and Stieglitz* [2014]. Modeled streamflow values from the first year are used for model spin-up. From the remaining 19 years of record, streamflow values of the first 9 years (water year 1972 to 1980) are used for model calibration and those of the next 10 years (water year 1981 to 1990) are used for model validation. Nash-Sutcliffe efficiency (NS) of square root transformed values of daily streamflow (see *Oudin et al.* [2006b]) is used as the objective function for calibration:

$$NS = 1 - \frac{\sum_{i=1}^{n}(\sqrt{Q_{obs,i}} - \sqrt{Q_{pred,i}})^2}{\sum_{i=1}^{n}(\sqrt{Q_{obs,i}} - \sqrt{\overline{Q}_{obs}})^2} \quad (1)$$

where, $Q_{pred,i}$ and $Q_{obs,i}$ are the predicted and observed streamflow values (L T^{-1}) on the i^{th} day respectively, $\overline{Q}_{obs}$ is the mean of all observed streamflow values (L T^{-1}), and n is the total number of days in the time series. We also use the water balance error (WBE) metric, in addition to NS, for the evaluation of model performance:

$$WBE = \frac{\sum_{i=1}^{n} Q_{pred,i} - \sum_{i=1}^{n} Q_{obs,i}}{\sum_{i=1}^{n} Q_{obs,i}} \times 100 \quad (2)$$

Following *Das et al.* [2008], the measure of model performance at a given catchment is obtained as an average of NS (and WBE) values from the calibration and validation model runs. The same calibration procedure is used for both lumped and distributed versions of the model.

3.2 Spatially lumped and spatially distributed model configuration

Each catchment is considered as a single areal unit for the lumped model and as a collection of multiple smaller areal units for the distributed model. Following *Wigington et al.* [2013], the smaller areal units within each catchment (henceforth referred to as landscape units) are delineated as first order sub-watersheds and incremental watersheds (Figure 3). For each catchment, we first extract the stream network from the USGS National Elevation Dataset's 30 m DEM using a 25 km^2 minimum drainage area threshold for channel initiation. Landscape units are then delineated such that each unit consists of a single stream channel and a contributing local hillslope. As such, the landscape units developed here are analogous to the

Representative Elementary Watersheds (REWs) of *Reggiani et al.* [1999] or the assessment units of *Wigington et al.* [2013].

For the lumped model, the daily precipitation and air temperature time series are obtained by calculating an areal average of the values from meteorological grids that are either fully or partially located within the catchment's drainage area. For the distributed model, the above procedure is repeated at each individual landscape unit to obtain the spatially variable precipitation and air temperature data in each catchment. Thus, if a particular catchment has 20 landscape units, then 20 distinct sets of the meteorological input data are created. To obtain simulated stream flows, the lumped model is run in its original configuration with one-dimensional meteorological input data [*Patil and Stieglitz*, 2014]. For the distributed configuration, the EXP-HYDRO model is first run independently at each landscape unit (with local meteorological input data). The streamflow output from all landscape units is then aggregated to obtain catchment streamflow using the following formula:

$$q_{catchment} = \frac{\sum_{i=1}^{N} q_i \cdot A_i}{\sum_{i=1}^{N} A_i} \qquad (3)$$

where, $q_{catchment}$ is the streamflow at catchment outlet (L T^{-1}), N is the total number of landscape units within the catchment, and q_i and A_i are the streamflow (L T^{-1}) and drainage area (L^2) respectively of landscape unit i (i = 1, 2, …, N). It is important to note the following two assumptions that are made in the distributed model: (1) channel network routing is ignored, i.e., the runoff generated from a landscape unit is assumed to reach the catchment outlet on the same day, and (2) all six calibration parameters of the EXP-HYDRO model are assumed to be same in every landscape unit within the catchment. Thus, the distributed EXP-HYDRO model presented here is essentially the same as its lumped counterpart; the only difference being the spatially distributed meteorological inputs. Moreover, since the lumped and distributed models are calibrated separately at each catchment, the optimal parameter values are likely to be different for either configuration.

3.3 Metrics of spatial climate variability

We use two different metrics to quantify the spatial variability of climate within a catchment: (1) moisture homogeneity index, and (2) temperature variability index. Below, we describe how each of these indices is calculated for our study catchments.

For the moisture homogeneity index (I_M), we first classify the climate of each landscape unit based on the Feddema climate classification [*Feddema*, 2005]. This classification system uses a modified version of the Thornthwaite moisture index [*Thornthwaite*, 1948] as follows:

$$I_f = \begin{cases} 1 - PET/P, & if \quad P > PET \\ 0, & if \quad P = PET \\ P/PET - 1, & if \quad P < PET \end{cases} \tag{4}$$

where, I_f is the Feddema moisture index whose values vary between -1 and 1, and P and PET are the mean annual precipitation and potential evapotranspiration respectively (derived from the long-term data of Climate Source, Inc.; see Section 2). Following *Wigington et al.* [2013], we calculate the I_f values of each landscape unit and classify the units into one of the following six moisture classes: "V" (very wet, $I_f \geq 0.66$), "W" (wet, $0.66 > I_f \geq 0.33$), "M" (moist, $0.33 > I_f \geq 0$), "D" (dry, $0 > I_f \geq -0.33$), "S" (semi-arid, $-0.33 > I_f \geq -0.66$), and "A" (arid, $-0.66 > I_f$). The moisture homogeneity index I_M is then calculated as the percent areal coverage of the moisture class that has the maximum amount of area within the catchment. Thus, if a given catchment has completely homogeneous climate, all landscape units in that catchment will belong to the same moisture class and the catchment will have an I_M value of 100%. Any value of I_M that is less than 100% is indicative of spatial variability of moisture within the catchment.

For the temperature variability index (I_{TV}), we first obtain the mean annual temperature T for each landscape unit (derived from the long-term data of Climate Source, Inc.; see Section 2). I_{TV} (unit: °C) is then calculated for each catchment with the following formula:

$$I_{TV} = \max(T_1, T_2, \ldots, T_N) - \min(T_1, T_2, \ldots, T_N) \quad (5)$$

where, N is the total number of landscape units within the catchment.

4 Results

We first analyze the differences in simulation performance between the lumped and distributed versions of the EXP-HYDRO model at all 41 study catchments. Figure 4a shows a 1:1 comparison of the NS values obtained with the lumped and distributed models. In most catchments (38 out of 41) the distributed model has improved NS values than the lumped model, although for 25 catchments the improvement is modest (< 10%). NS values for the lumped model vary from 0.29 to 0.94, with a median value of 0.70. On the other hand, NS values for the distributed model vary from 0.32 to 0.94, with a median value of 0.79. The percentage improvement in NS values with the distributed model ranges from -0.12% to 49.67%, with a median improvement of 6.63%. Out of the 41 catchments in total, 13 catchments show NS improvement of greater than 10% with the distributed model. There are only three catchments for which the distributed model has lower NS values than the lumped model, but with very small amounts of deterioration (-0.12%, -0.11%, and -0.03%). Figure 4b shows a 1:1 comparison of the WBE values obtained with the lumped and distributed models. For the majority of catchments (with the exception of two outliers), the WBE values are located close to, and scattered on both sides of, the 1:1 line. The two outlier catchments in Figure 4b are located in the eastern drier region of Oregon. Both lumped and distributed models perform poorly at these catchments (NS < 0.4). Therefore, we suspect that the big deviation of WBE values might be arising from poor parameter identification at these catchments, rather than any physical reason. The overall results from Figure 4 suggest that, unlike NS, there appears to be no systematic difference between the lumped and distributed model in terms of the WBE metric.

Next, we examine the improvement in model performance achieved by the distributed model within the context of long-term spatial climate variability in a catchment. For the purpose of this analysis, we define model performance improvement as the % improvement in NS obtained with the distributed model at each catchment. The two metrics of spatial climate variability, I_M and I_{TV}, show considerable range among our study catchments. I_M varies from 38.1% to 100%, with a median value of 78.7%; whereas I_{TV} varies from 0.7 °C to 8.1 °C, with a median value of 3.5 °C. Figures 5a and 5b show the relationship of % NS improvement with I_M and I_{TV}, respectively. Both these relationships are also fit with a non-linear quadratic model to determine how much of the variance in % NS improvement can be explained by each metric. High performance improvement is observed for catchments with low I_M values (i.e., low homogeneity of moisture distribution), and the amount of improvement declines with increasing I_M value (Figure 5a). However, this declining pattern is observed only among catchments with relatively low moisture homogeneity ($I_M < 80\%$). The relationship between % NS improvement and I_M becomes scattered for the more homogeneous catchments ($I_M > 80\%$). The highest variability of % NS improvement is observed in completely homogeneous catchments (

$I_M = 100\%$). For the metric I_{TV}, greater improvement in model performance is observed for higher I_{TV} values (Figure 5b). Nonetheless, the relationship shows a high degree of scatter, especially for higher values of I_{TV}. R^2 value of the non-linear quadratic fit (red dashed line in Figures 5a and 5b) is 0.25 for the relationship of % NS improvement with I_M and 0.36 for the relationship of % NS improvement with I_{TV}.

Since Figure 5a shows a noticeably different behavior for catchments with $I_M < 80\%$ than for those with $I_M > 80\%$, we segregate them into two distinct groups, henceforth referred to as Group 1 ($I_M < 80\%$, n = 21) and Group 2 ($I_M > 80\%$, n = 20) catchments. Figure 6 shows the location of both Group 1 and Group 2 catchments. Group 1 catchments are mostly located in the central drier parts of the PNW; although there are a few along the Oregon Coast range and the Rocky Mountains. Most of the Group 2 catchments are located in the wetter parts of the PNW, along the western sides of the Cascade and Rocky Mountain ranges; a few are located along the coastal mountains near the Pacific coast. Mean annual precipitation varies from 540 mm to 2340 mm (median = 935 mm) in Group 1 catchments, and from 812 mm to 3615 mm (median = 1690 mm) in Group 2 catchments. We further examine the relationships of % NS improvement with I_M and I_{TV} separately for each group. Figures 7a and 7b show the relationship of % NS improvement with I_M and I_{TV} respectively for the Group 1 catchments. A distinct and inversely proportional relationship is observed between % NS improvement and I_M (R^2 = 0.46). On the other hand, a directly proportional but weaker (R^2 = 0.21) relationship is observed between % NS improvement and I_{TV}. In sharp contrast, for Group 2 catchments (Figures 7c and 7d), we find that virtually no relationship exists between % NS improvement and

I_M (R^2 = 0.04), whereas a strong non-linearly increasing relationship (R^2 = 0.70) exists between % NS improvement and I_{TV}.

5 Discussion

Results show that the distributed version of EXP-HYDRO model performs better than its lumped counterpart in 38 out of 41 catchments, and noticeably better (>10% NS improvement) in 13 out of 41 catchments. This finding clearly demonstrates the importance of incorporating spatially distributed meteorological inputs into hydrologic models, at least for certain types of catchments. In a study similar to ours, *Vaze et al.* [2011] compared the lumped and distributed versions of four hydrologic models at 240 catchments in southeast Australia. Contrary to our results, they found that only marginal improvement occurred with distributed models, and most of it in larger catchments (>1000 km^2). However, *Vaze et al.* [2011] did not simulate snow processes in their hydrologic models, and they also did not quantify the spatial climate variability in their study catchments. Figure 8 shows the relationship of drainage area and % NS improvement for our study catchments. This relationship is highly scattered and exhibits no particular trend, which suggests that drainage area does not necessarily inform us about spatial climate variability within a catchment.

Within the context of the PNW region (Figure 6), the two metrics of spatial climate variability seem to provide complementary information. Specifically, the moisture homogeneity index (I_M) represents the spatial variability of wetness, i.e., the competition of precipitation input and evaporative demand, in a catchment. On the other hand, the temperature variability index (I_{TV}) appears to represent the spatial variability of precipitation phase (rain vs. snow) in a catchment. Figure 9 shows the relationship between I_{TV} and the lowest observed mean annual temperature (amongst all landscape units) within a catchment. This relationship has a significant declining trend ($R^2 = 0.59$, $p < 0.01$), and shows that catchments with high I_{TV} values tend to have very low (near or below freezing) values of mean annual temperature in their coldest landscape unit. This suggests that catchments with high I_{TV} values (i.e., high temperature variability) are also likely to have high spatial variability of precipitation phase. Interestingly, results show that neither I_M nor I_{TV} alone is sufficient to explain whether a particular catchment will benefit from the use of a distributed model (Figures 5a and 5b). However, the combined use of both these metrics provides a much better understanding of the types of catchments for which the distributed model provides better streamflow predictions. A logical expectation would be that catchments with low moisture homogeneity (low I_M) will have the largest % NS improvement, and this improvement will reduce as we move towards catchments with more homogeneous moisture distribution (high I_M). We do observe this trend, but only among the Group 1 catchments (Figure 7a). Moreover, compared to I_M, I_{TV} has a weaker relationship with % NS improvement for Group 1 catchments (Figure 7b). This suggests that for catchments with relatively low moisture homogeneity, the spatial variability of wetness is a better indicator of performance improvement with a distributed model than the spatial variability of precipitation phase. A completely opposite behavior is observed for Group 2 catchments ($I_M > 80\%$). For these catchments, I_M has virtually no explanatory power of % NS improvement (Figure 7c), whereas I_{TV} has a substantially higher explanatory power (Figure 7d). This suggests that for catchments with high moisture homogeneity, the spatial variability of precipitation phase is a better indicator of performance improvement with a distributed model than the spatial variability of wetness.

Figure 10 shows the thirteen catchments for which more than 10% NS improvement is obtained with the distributed model. Of these, the seven Group 2 catchments with high wetness homogeneity are located in wetter regions of the PNW (Olympic Peninsula, and the western flanks of the Cascade and Rocky Mountains) where all parts of the catchment receive high amounts of precipitation. However, the steep elevation gradients in these regions create substantial spatial variability in air temperature [*Jefferson*, 2011; *Leibowitz et al.*, 2012; *Nolin and Daly*, 2006]. This is reflected in the high I_{TV} values observed at most of these catchments (Figure 7d). While spatially uniform meteorological inputs might provide good enough estimate of precipitation amount in some cases, they are likely to miss the spatial variability of precipitation phase. Use of lumped models in such catchments can lead to erroneous estimation of the amount of snow accumulation and the timing of snowmelt. Thus, a spatially distributed representation of meteorological inputs appears to be important in catchments where heterogeneous precipitation phase is a significant factor (even if the same amount of precipitation occurs in the rain and snow dominated areas). Capturing the spatial variability of precipitation phase is even more critical in the wet mountainous areas of the PNW because most climate change projections forecast a high vulnerability to the amount and the extent of snow accumulation in those parts [*Nolin and Daly*, 2006; *Regonda et al.*, 2005; *Salathé et al.*, 2008; *Sproles et al.*, 2013]. It is worth mentioning here that several hydrologic modeling studies have also accounted for spatially variable precipitation phase by discretizing catchments in the vertical dimension based on elevation bands [*Abdulla and Lettenmaier*, 1997; *Hartman et al.*, 1999; *Parajka and Blöschl*, 2008]. Although beyond the scope of our study, it would be interesting to compare how well the spatial variability of climate is represented when a catchment is discretized in the vertical dimension (elevation bands) instead of horizontal dimension (subcatchments). The six Group 1 catchments in Figure 10 are located in the drier central parts of the PNW. Catchments in this region typically contain rivers that are fed by a smaller headwater area that receives most of the precipitation and flow downstream into a larger semi-arid landscape [*Wigington et al.*, 2013]. Distributed models have an obvious advantage in these catchments because a lumped representation of the meteorological inputs is likely to misestimate both precipitation phase and magnitude.

A number of assumptions and simplifications were made in our methods that could potentially influence the findings of this study. For the distributed EXP-HYDRO model, we used the same parameter values in all landscape units. This simplification essentially ignores the spatial variability of catchment properties such as land use, geology, and soil type, which can play an important role in the filtering of spatially variable rainfall input. Numerous studies with event scale hydrologic models have shown that a catchment's ability to dampen the rainfall signal is an important indicator of whether a distributed model will perform better during a spatially variable rainfall event [*Arnaud et al.*, 2002; *Obled et al.*, 1994; *Segond et al.*, 2007; *Smith et al.*, 2004]. It is not clear though whether (and how) the heterogeneous catchment properties will dampen the effects of spatially variable meteorological inputs for continuous streamflow prediction. We also ignored channel network routing for the distributed EXP-HYDRO model. The assumption here was that the runoff generated from all landscape units reaches the catchment outlet on the same day. While we did choose catchments within a limited range of drainage area (500 km^2 to 5000 km^2) to mitigate the effects of this assumption, it is possible that some catchments might benefit more than others by the use of distributed model with explicit channel network routing. We used a gridded meteorological dataset [*Maurer et al.*, 2002] to generate both the lumped and distributed inputs for all catchments. The spatial resolution and quality of this dataset has a huge influence on how well we can characterize the spatial variability of meteorological inputs in our catchments. While the *Maurer et al.* [2002] data has been used extensively in many hydrologic studies, it must be acknowledged that precipitation estimates are usually poorer at high elevations and in regions with fewer meteorological stations. The choice of using two specific climate variability metrics (I_M and I_{TV}) also influenced the way in which our results were interpreted. For I_M, we were in many ways building on the hydrologic classification work of *Wigington et al.* [2013] and chose the areal dominance concept (of climate class) as a measure of homogeneity. Alternate metrics such as Shannon's diversity index [*Shannon*, 1948] or the standard deviation of I_f could have served a similar function, but we chose I_M due to the high physical realism of its numerical values. For I_{TV}, our goal was to highlight the maximum extent of the spatial temperature contrast within each catchment; especially because high elevation gradients in some parts the PNW create distinct elevation divides for snow vs. rain type precipitation in the winter months. Alternate metrics such as the standard deviation of air temperature could have also provided a function similar to I_{TV}. We only used one type of model structure (EXP-HYDRO) to test the effects of lumped and distributed meteorological inputs. While the use of a different model might provide different quality of simulation performance, we think that similar findings (as of our study) are likely to be obtained by using other commonly used hydrologic models. Moreover, studies with multi-model assessments over a large number of catchments have shown that the geographic patterns of hydrologic predictability tend to be more or less similar for models that include the same hydrological processes [*Oudin et al.*, 2008; *Vaze et al.*, 2011].

6 Conclusions

In this paper, we compared the streamflow simulation performance of lumped and distributed versions of the EXP-HYDRO model at 41 catchments in the Pacific Northwest region of USA. Results showed that the distributed model performs better than the lumped model in most (38 out of 41) catchments. Performance improvement using the distributed model (in comparison to the lumped model) was further analyzed with respect to two metrics of spatial climate variability in a catchment, viz., moisture homogeneity index (I_M) and temperature variability index (I_{TV}). We found that for catchments with low moisture homogeneity ($I_M < 80\%$), I_M was a better predictor of model performance improvement than I_{TV}. Such catchments are more likely to be located in dry regions with small headwater areas that supply most of the water. A completely opposite trend was observed among catchments with high moisture homogeneity ($I_M > 80\%$), most of which were located in the wetter areas of the PNW. Based on the results presented this study, we conclude that the use of spatially distributed meteorological inputs in hydrologic models has the potential to substantially improve streamflow predictions, at least for certain types of catchments. Catchments with highly variable moisture distribution are the obvious candidates for using spatially distributed meteorological inputs in a hydrologic model. On the other hand, homogeneously wet catchments can greatly benefit from spatially distributed meteorological inputs if there is high spatial variability of precipitation phase. Our assumption of spatially uniform model parameter values within a catchment ensured that any improvement obtained with the distributed model was solely based on the spatially distributed representation of meteorological inputs. However, this assumption will have to be relaxed for future investigations of the effects of spatially variable land use, soil types, and/or geology on catchment streamflow predictions.

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Figures:

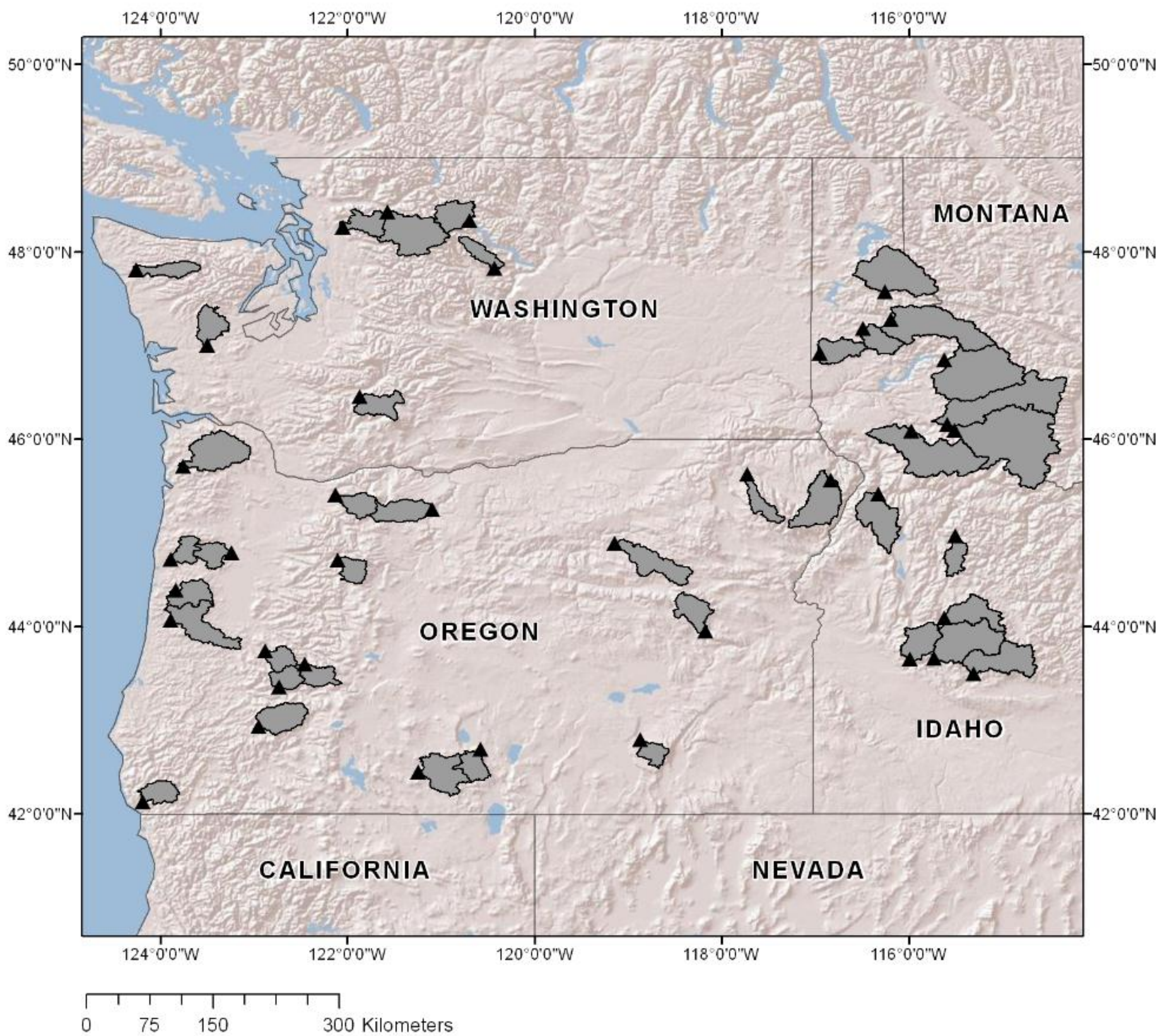

Figure 1: Location of the 41 study catchments. Black triangles are the catchment outlets, whereas gray regions are the drainage areas.

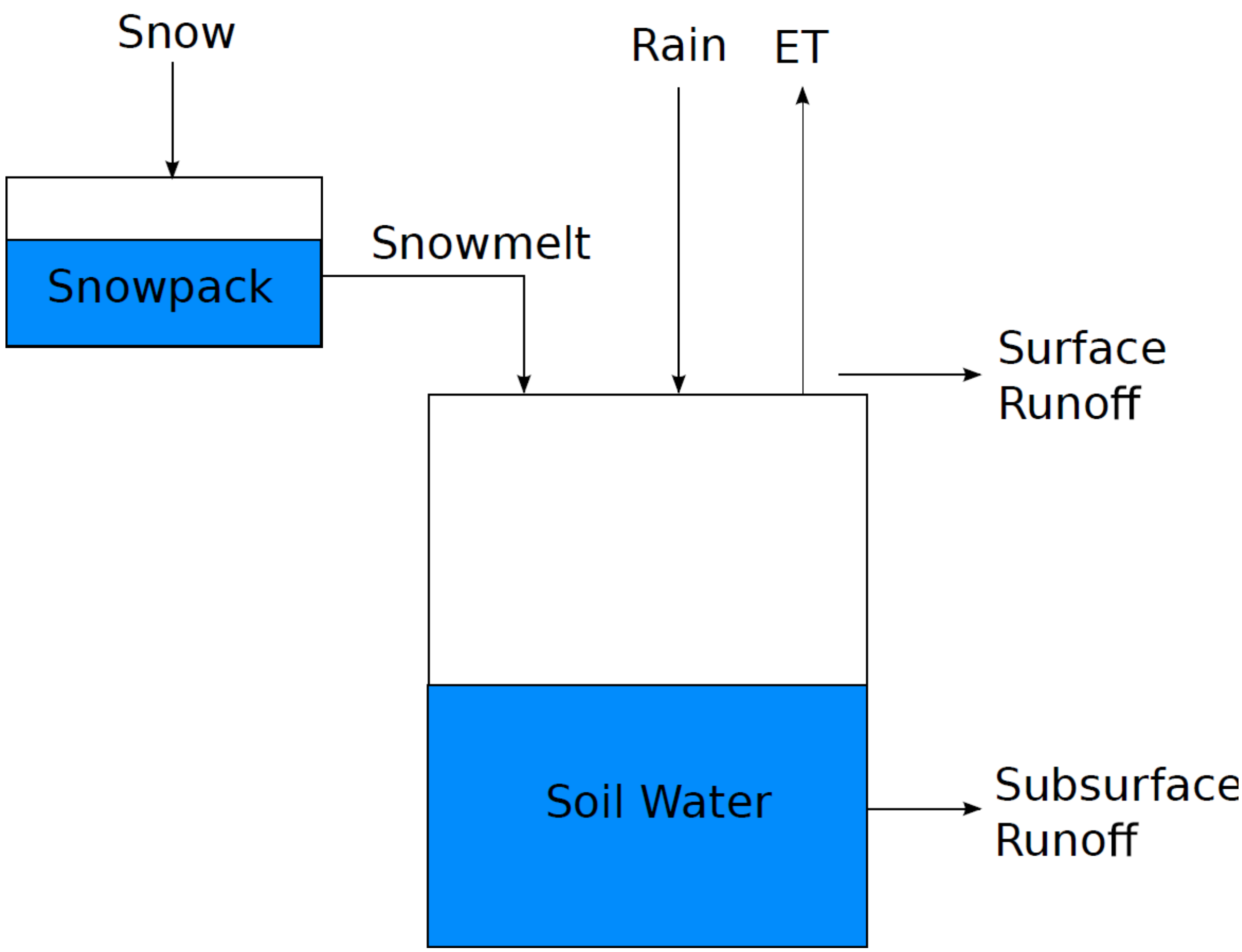

Figure 2: Schematic representation of the EXP-HYDRO model.

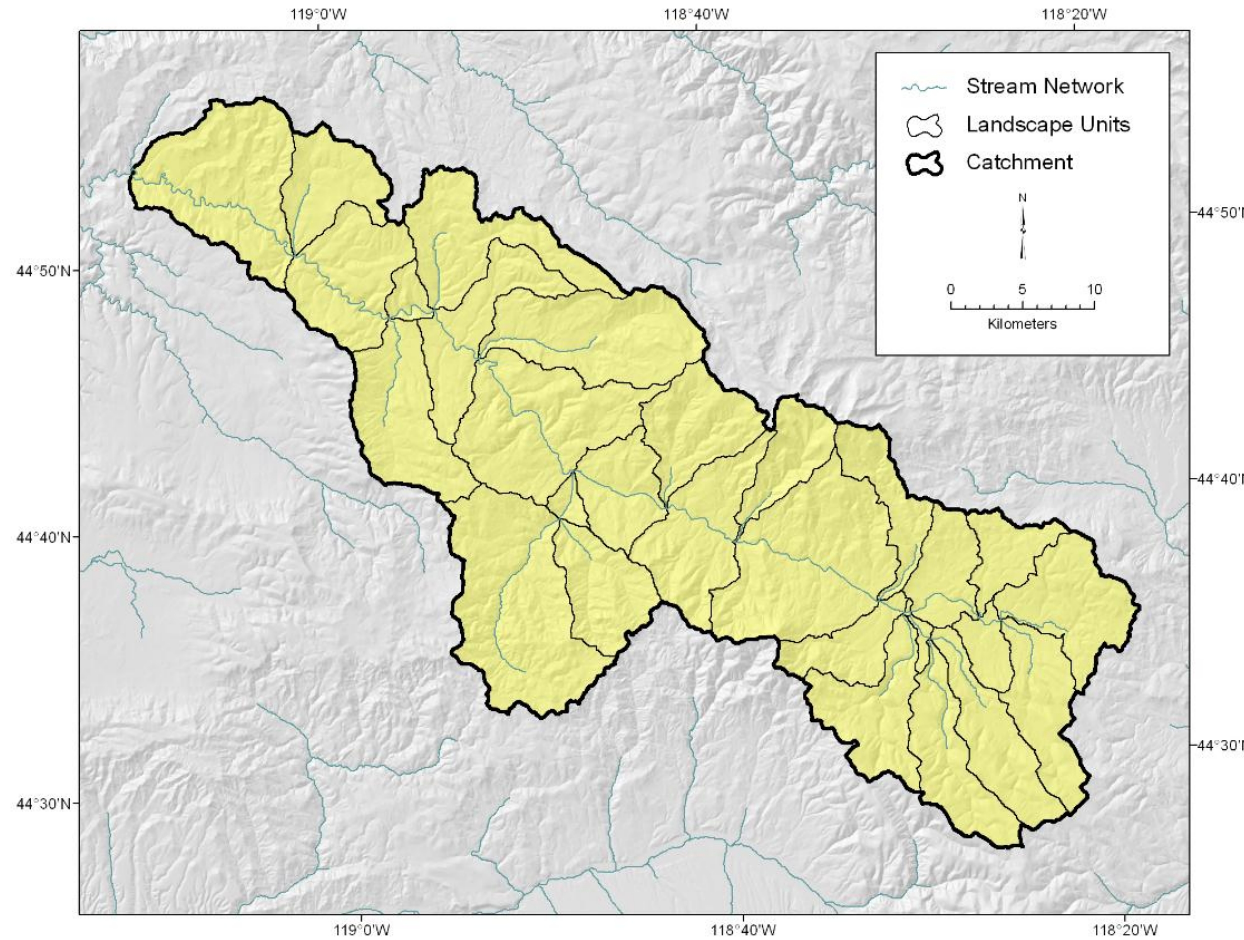

Figure 3: Representation of the individual landscape units within a catchment.

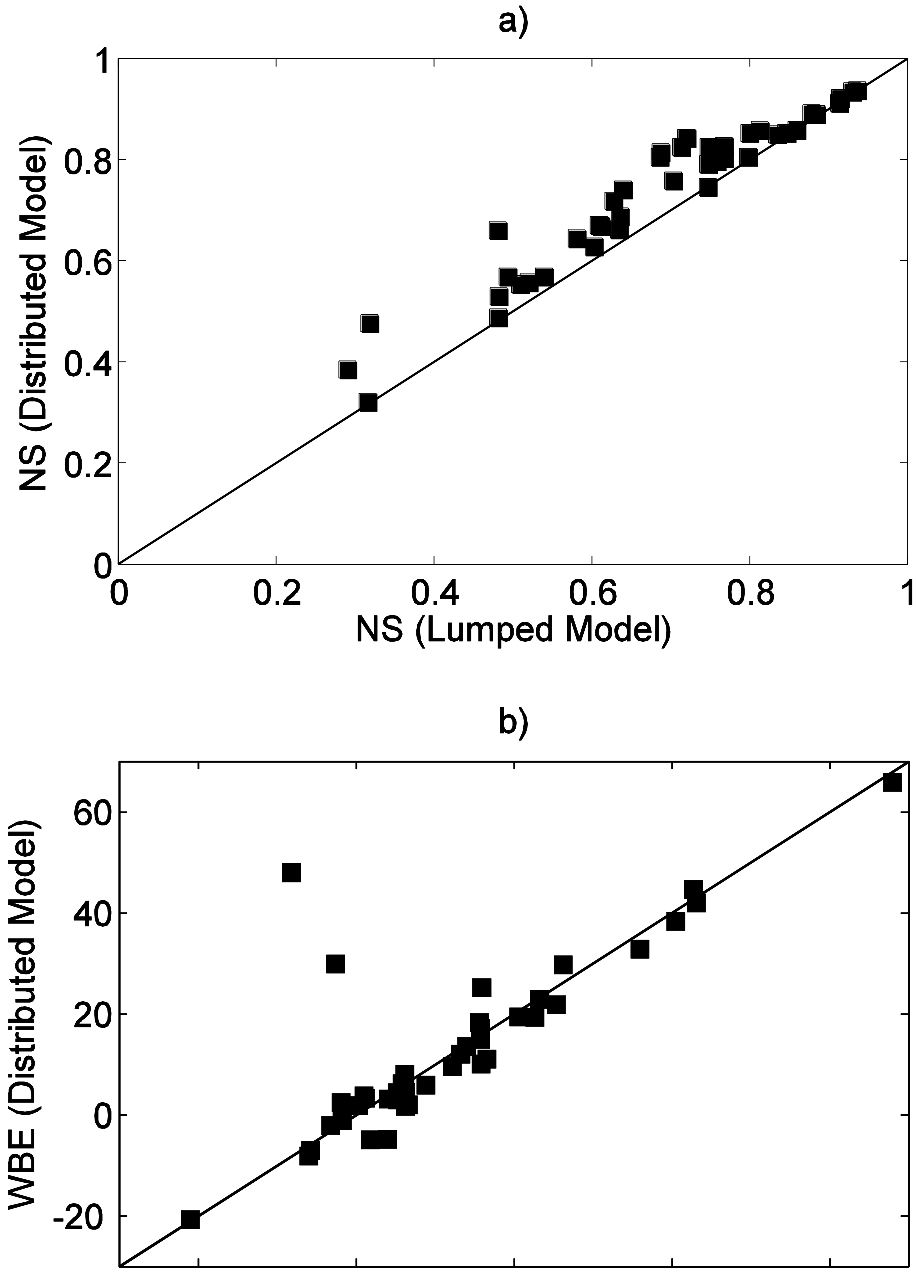

Figure 4: A one-on-one comparison between lumped and distributed EXP-HYDRO model with a) Nash-Sutcliffe efficiency (NS), and b) Water Balance Error (WBE).

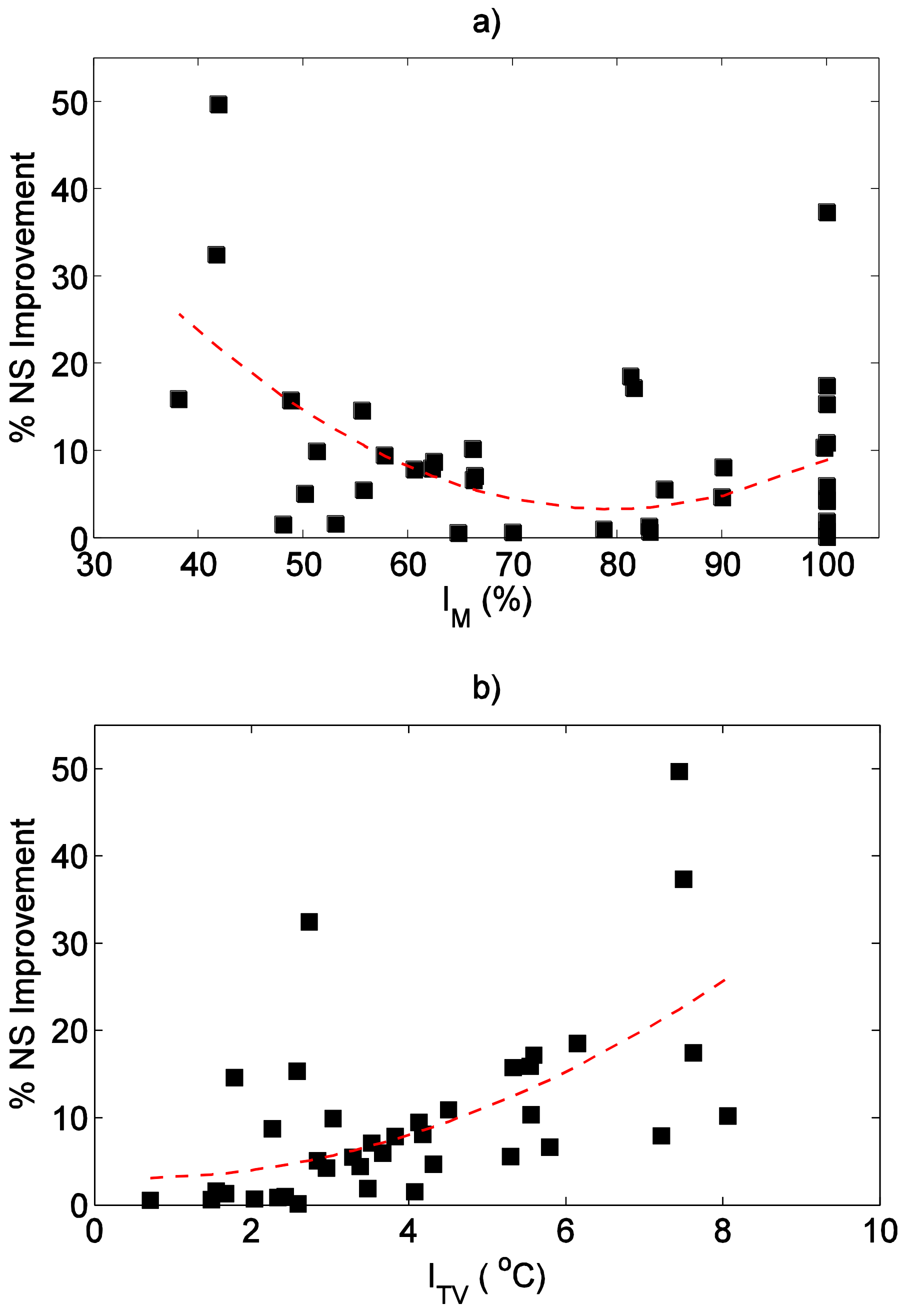

Figure 5: Relationship of model performance improvement with a) I_M , and b) I_{TV} . Red dashed line is the regression fit using quadratic equation.

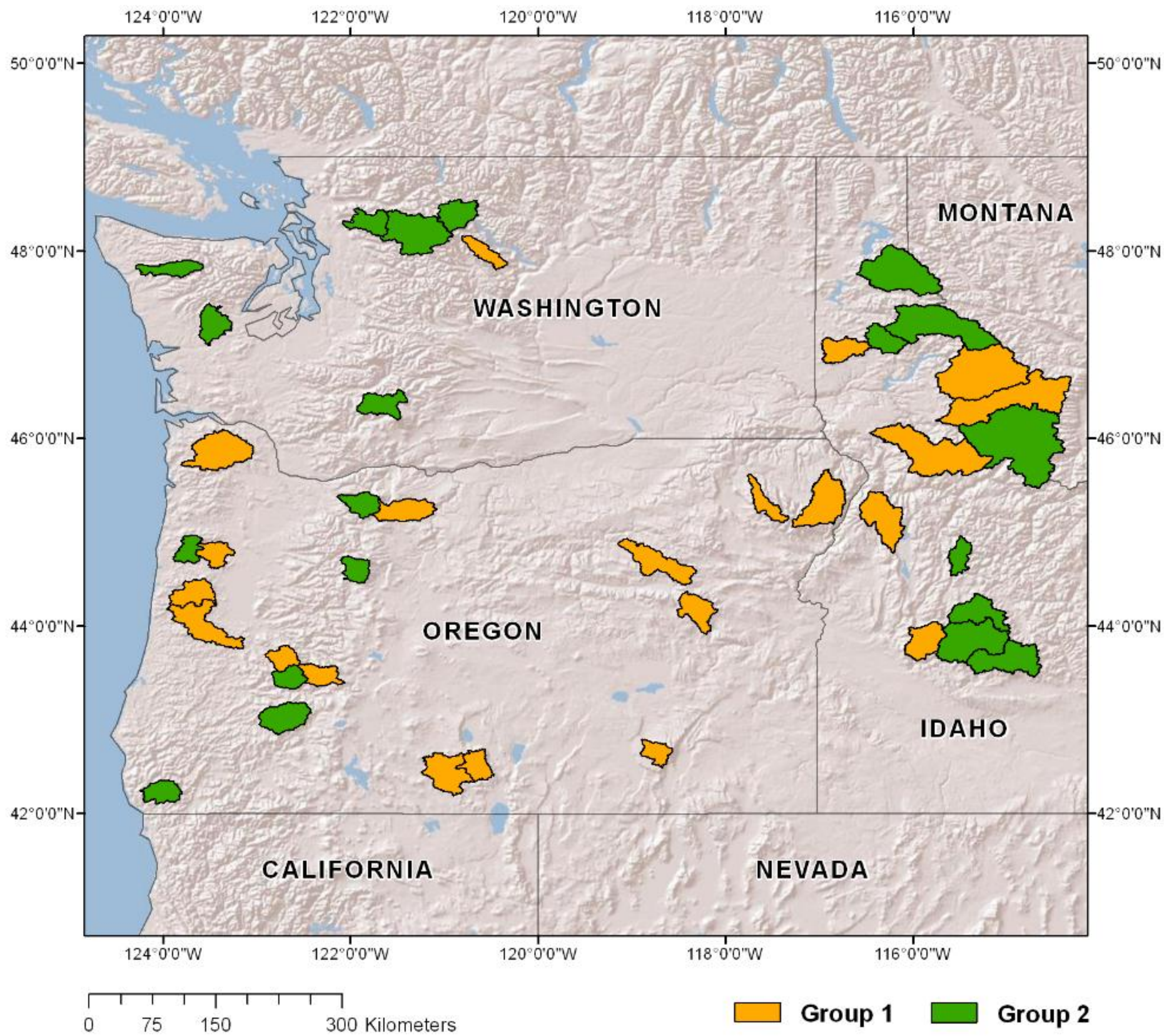

Figure 6: Location of the Group 1 ($I_M < 80\%$) and Group 2 ($I_M > 80\%$) catchments.

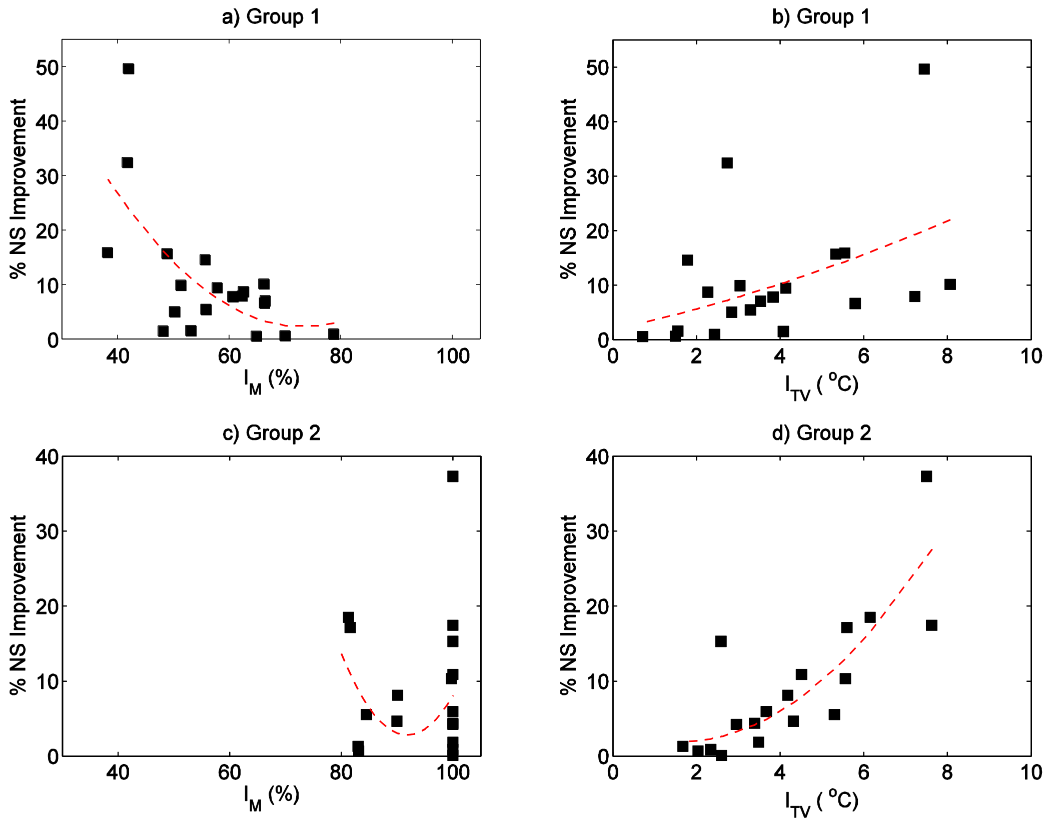

Figure 7: Relationship of model performance improvement with I_M and I_{TV}, shown separately for the Group 1 and Group 2 catchments. Red dashed line is the regression fit using quadratic equation.

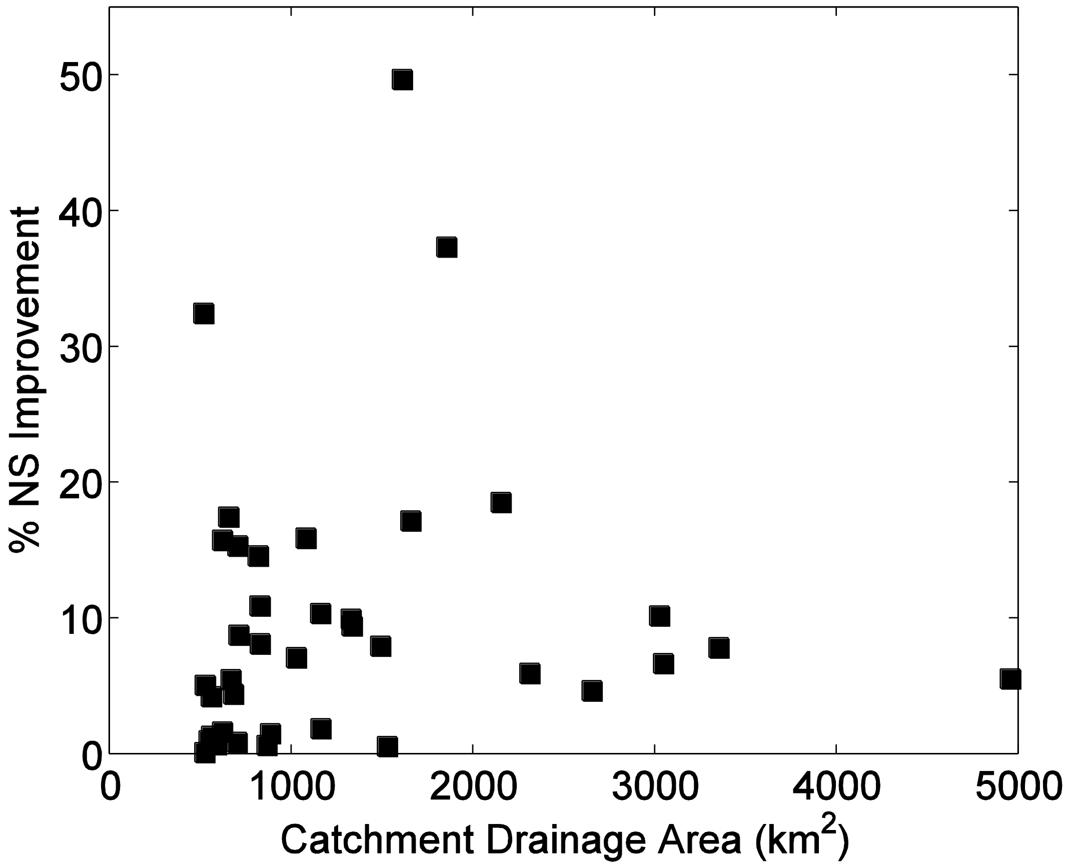

Figure 8: Relationship of model performance improvement with catchment drainage area.

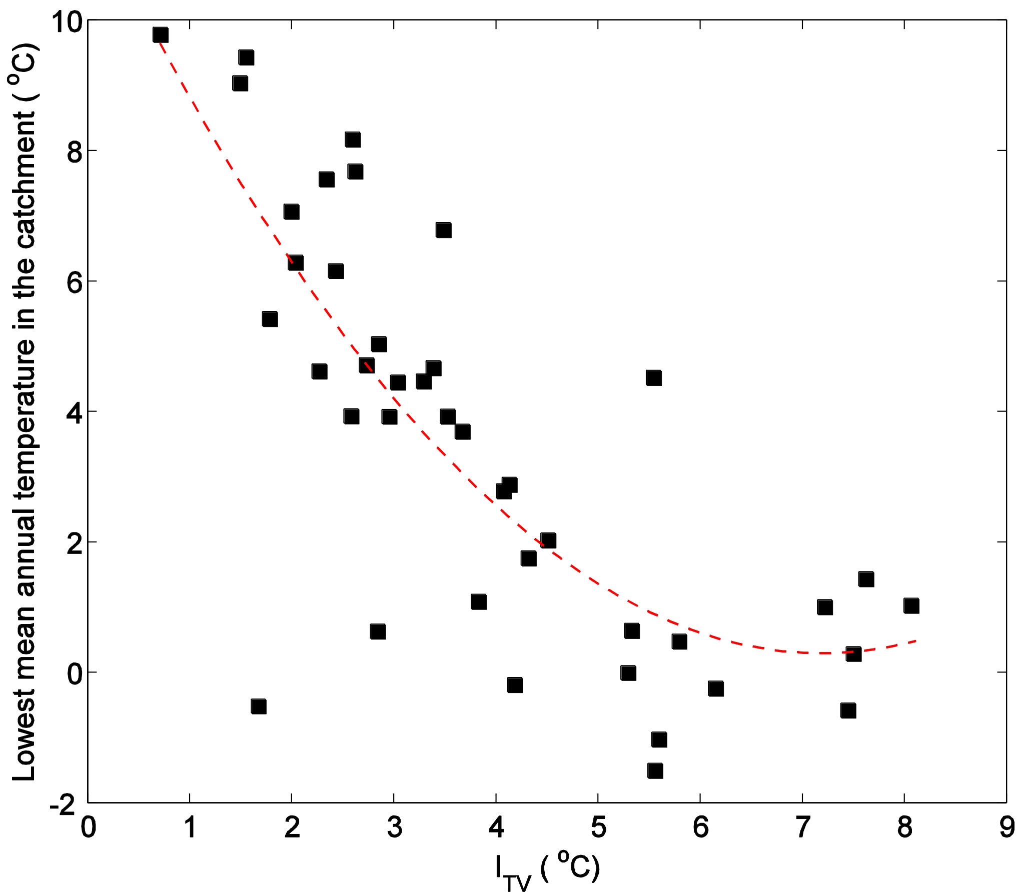

Figure 9: Relationship between I_{TV} and the lowest mean annual temperature within the catchment. Red dashed line is the regression fit using quadratic equation.

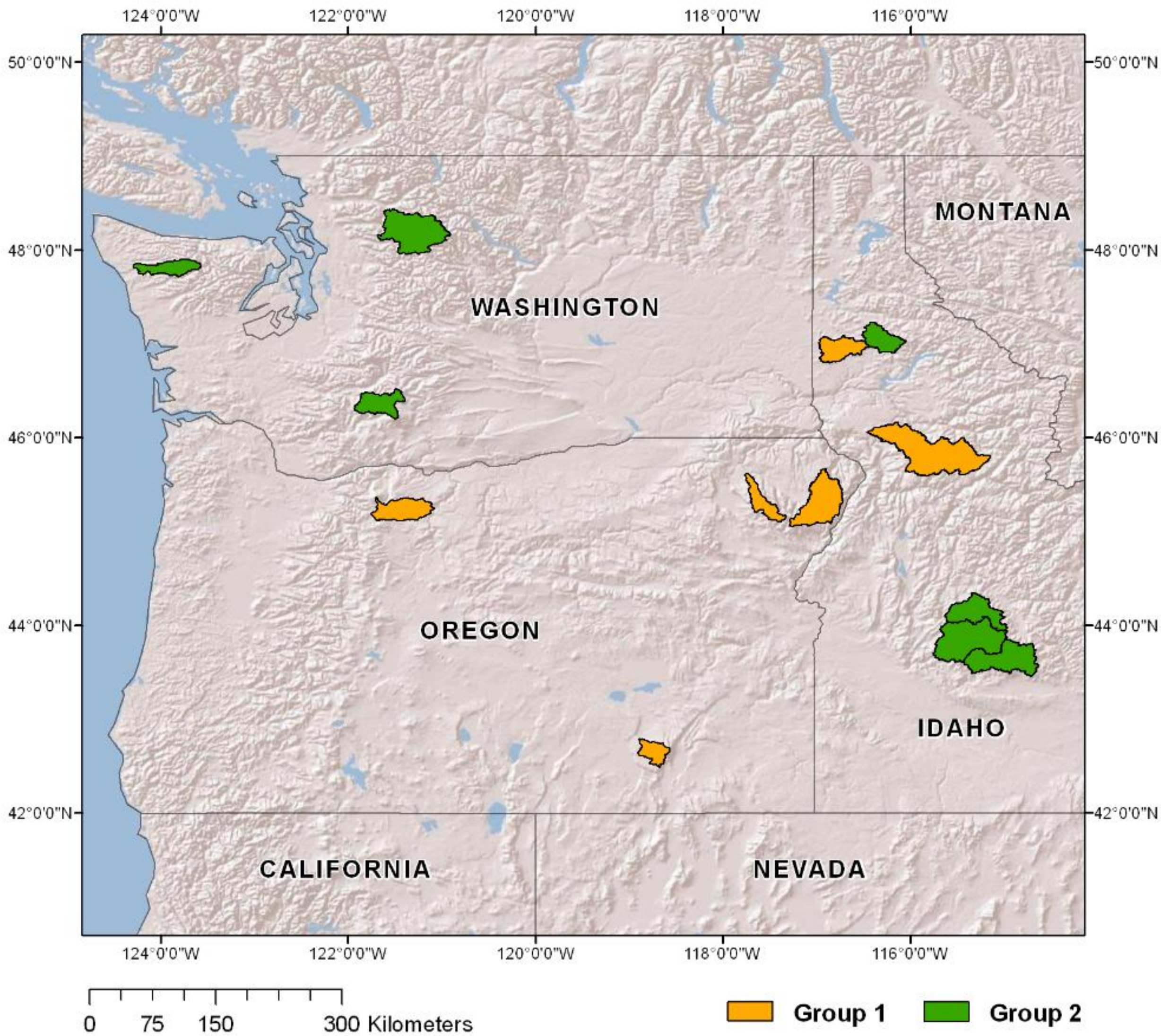

Figure 10: Location of the catchments where distributed model shows more than 10% NS improvement. Group 1 and Group 2 catchments are shown separately.